TIME SCALING and FREQUENCY INVARIANT MULTIRESOLUTION ANALYSIS OF ULTRASONIC NDE SIGNALS

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INTRODUCTION

Nuclear power plant pipes are periodically inspected for possible cracks that occur in the heat-affected zones of welds. Intergranular stress corrosion cracks (IGSCC) are the most common type of cracks encountered particularly in stainless steel piping. Three major factors are required for the formation and propagation of IGSCCs, the tensile stress on the inner diameter of the weld region, a corrosive environment and a sensitized grain structure. When these flaws are not detected early enough, the consequences can be disastrous, and therefore the detection of IGSCCs is of significant interest to the nuclear industry.

Ultrasonic techniques have been successfully used for the inspection of these flaws for years. These techniques involve launching an ultrasonic waveform into the specimen under inspection, and analyzing the signals reflected from discontinuities that are present in the specimen. One of the main challenges ultrasonic inspectors face is that signals reflected from cracks are very similar to signals reflected from other discontinuities that may be due to the geometry of the pipe. Counterbores and rootwelds are two such discontinuities that are present in the vicinity of the weld area. A schematic of the weld geometry illustrating these discontinuities is depicted in Figure 1. Since large volumes of such piping weld inspection data need to be analyzed in nuclear power plants, the availability of an automated signal classification (ASC) scheme can help in providing accurate and consistent signal interpretation.

One of the major concerns in the development of ASC systems is the choice of transducer center frequency. Higher frequency ultrasonic signals are able to resolve reflections from reflectors that are close to each other better than low frequency signals. However, higher frequency signals attenuate much faster than the lower frequency signals, and therefore, they are not useful when the thickness of the pipe is large enough to make attenuation a significant problem. Consequently, inspectors usually scan the specimens with transducers of different frequencies in an attempt to obtain as much information as possible. Signals of different frequencies, however, pose a major problem to ASC schemes, since these schemes are usually based on a measure of similarity between the waveforms, and signals of different frequencies look considerably different even if they belong to the same class of reflection.

The main purpose of this study is to develop an ASC scheme that would be insensitive to the frequency of operation. Such a scheme was developed using a three step approach: (i) a preprocessing step to obtain *frequency invariance* by mapping signals of different frequencies to a single reference frequency, (ii) a feature extraction procedure based on multiresolution analysis using discrete wavelet transform, and finally (iii) a neural network classification scheme to obtain the class of the reflector.

Initial studies on automated signal classification schemes for NDE applications date back to seventies when Rose and his colleagues used pattern recognition techniques to characterize ultrasonic NDE signals [1]. Various sets of features selected from time and frequency domains, as well as from the physical properties of signals, have been used for characterizing ultrasonic signals [2], [3]. A number of signal classification algorithms have also been used for characterization of ultrasonic weld inspection signals, ranging from simple clustering algorithms such as K-Means, to sophisticated supervised techniques such as multilayer perceptron or fuzzy Artmap.

APPROACH

A three step approach has been used in order to obtain frequency invariant characterization of ultrasonic weld inspection signals. In the first step, frequency invariance is obtained using a technique called *time scaling*, which simply maps signals of different frequencies to corresponding signals at a reference frequency.

In the second step, the discrete wavelet transforms (DWT) of the time-scaled signals have been computed to obtain the most relevant features of the signals. DWT is a multiresolution analysis technique that provides the time-frequency representation of the signal to be analyzed. DWT is not only a suitable technique for analyzing time-localized signals such as the ultrasonic weld inspection signals, but it also is a very efficient technique for data reduction. In the third step, the DWT coefficients were used to train a multilayer perceptron (MLP) neural network. The trained network was then used to classify the ultrasonic weld inspection signals into one of the three classes, namely, crack, counterbore and rootweld.

Time Scaling

Ultrasonic weld inspections are usually carried out at multiple frequencies using different transducers in order to obtain as much information as possible. Higher frequency signals provide better resolution but they attenuate rapidly, and conversely, lower frequency signals penetrate deeper into the material but they cannot provide good resolution. ASC algorithms, however, rely on the shape of the signal, which can vary significantly with the frequency of operation. It is, therefore, required that the ASC system recognize signals of different frequencies and interpret them in such a manner that the overall performance is independent of the frequency of operation.

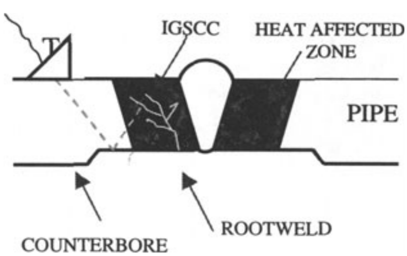

Figure 1. Weld geometry

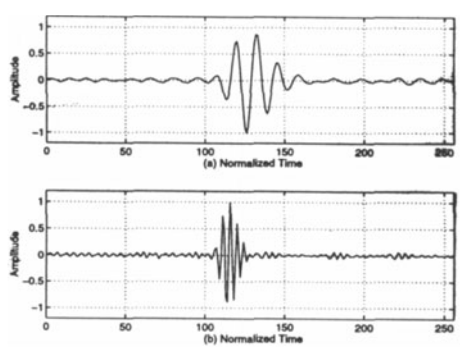

Figure 2. (a) 1 MHz signal
(b) 2.25 MHz signal

The most straightforward and common method used in such situations is to develop different ASC systems for different frequencies of interest. This method, apart from increasing the system complexity, is not suitable for the analysis of ultrasonic weld inspection signals due to the inherent variations in the frequencies of signals of the same transducer.

An alternate method is to shift all signals to the baseband centered at zero frequency. This method also fails to provide the required frequency invariance due to different bandwidths of signals at different frequencies. Figure 2 shows two signals at 1 MHz and 2.25 MHz with their corresponding frequency spectra given in Figure 3. It can be clearly seen that the bandwidth of the 2.25 MHz signal is greater than that of the 1 MHz signals, and consequently, baseband shifting fails to provide the desired frequency invariance. The spectra of the baseband-shifted signals are illustrated in Figure 4.

The method developed in this study is based on time scaling, a technique that transforms signals of different frequencies to corresponding signals at a reference frequency. In doing so, the spectra of signals are not only shifted to a reference frequency, but their spectra are compressed or stretched in such a manner that bandwidths are made equal, without changing the overall shape of the spectra. This transformation of signals of frequency f_1 to a frequency $f_2=f_1/a$, makes use of the Fourier transform property.

$$x(at) \Leftrightarrow \frac{1}{a} X(\frac{f}{a}) \qquad (1)$$

where $x(t) \Leftrightarrow X(f)$, and a is the scaling factor. Time scaling is accomplished by a combination of decimation and interpolation operations, where decimation by a factor of m drops every m^{th} *sample*, and interpolation by a factor of n adds n new samples of appropriate amplitude between each sample of the original signal. In this study, we performed time scaling on 2.25 MHz signals in order to transform them to a reference frequency of 1 MHz. The time scaling factor of 4 was therefore obtained by interpolating the 2.25 MHz signals by a factor of 9 and then decimating them by a factor of 4. This procedure effectively increases the number of samples by a factor of 2.25, and these signals are then truncated from each end in order to bring them to the original length. Due to the time localization of ultrasonic weld inspection signals, this truncation operation does not cause any major loss of information.

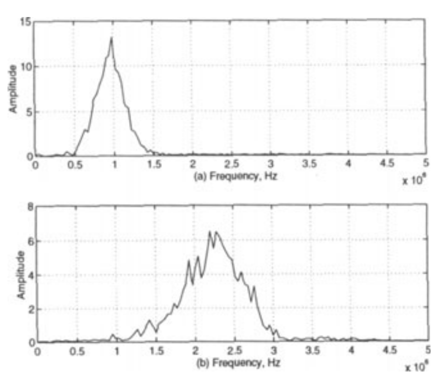

Figure 3. Frequency spectra of the signals in Figure 2.

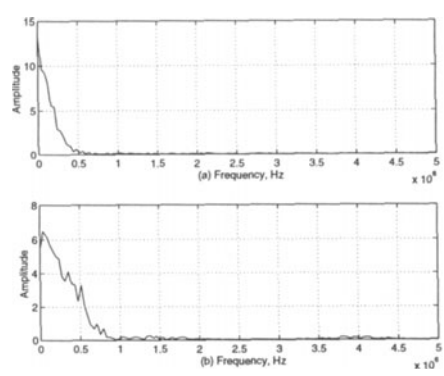

Figure 4. Baseband shifted spectrums.

The effect of time scaling on a typical signal is illustrated in Figure 5 and Figure 6, in time and frequency domains, respectively. Figure 5 (a) shows a reference 1 MHz signal, whereas Figure 5(b) shows the time scaled version of the 2.25 MHz signal shown in Figure 2(b). The spectra of these signals are illustrated in Figure 6. It can be seen that the spectrum of the 2.25 MHz signal has not only shifted to a center frequency of 1 MHz, but its overall shape is also compressed such that its bandwidth is similar to that of the 1 MHz signal. The time scaled single frequency signals are then used for feature extraction.

Feature Extraction: Discrete Wavelet Transform:

Discrete wavelet transform (DWT) is a multiresolution analysis technique that provides time-frequency representation of a signal by decomposing the signal into different frequency bands at different resolutions. DWT is a suitable technique for the analysis of time localized signals such as the ultrasonic weld inspection signals. The decomposition is obtained by using a scheme called *subband coding*. According to this scheme, the signal is first passed through a halfband highpass filter g[n] and a lowpass filter h[n], where g[n] and h[n] are quadrature mirror filters of each other. The filtered signals are then subsampled by a factor of 2 since they now span half the frequency band and therefore, half the number of samples are adequate to characterize them.
This constitutes one level of decomposition, and can be expressed as

$$
\begin{aligned}
y_{high}[k] &= \sum_n x[n].g[2k-n] \\
y_{low}[k] &= \sum_n x[n].h[2k-n]
\end{aligned}
\qquad (2)
$$

where $y_{high}[k]$ and $y_{low}[k]$ are the outputs of the highpass and lowpass filters, respectively, after subsampling by 2. The output of the highpass filter constitutes the Level 1 DWT coefficients, and the output of the lowpass filter is passed through the same lowpass and highpass filters for further decomposition. The decomposition continues until all samples are exhausted by subsapling. The DWT of the signal is then obtained by concatenating all DWT coefficients in the previous levels. The details of this algorithm can be found in [4].

Neural Network Classification

A variety of supervised and unsupervised pattern recognition algorithms are available for classification problems, among which neural networks have found increasing use in the last few decades. For classification of signals, the *multilayer perceptron (MLP)* neural network has enjoyed a considerable attention due to its ability to generate complex decision boundaries. The

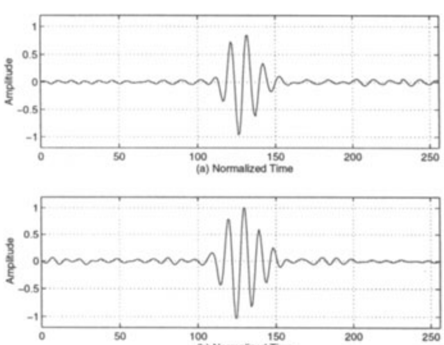

Figure 5. (a) 1 MHz signal.
(b) Scaled 2.25 MHz signal.

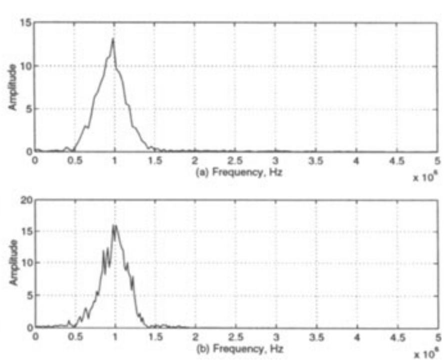

Figure 6. Frequency spectra of the signals in Figure 5.

MLP is trained using the learning algorithm called *the backpropagation (BP) learning rule.* The details of this algorithm can be found in [5].

In this study, we have used a two-hidden layer MLP with 128 input nodes, corresponding to the first 128 DWT coefficients of 256 sample long signals. The two hidden layers contained 30 and 7 nodes, respectively, and the output layer contained 3 nodes, one for each of the classes under consideration, namely crack, counterbore and rootweld.

RESULTS and DISCUSSION

Three databases containing weld inspection signals from nuclear power plant piping were used to evaluate the feasibility of the overall approach..

Database I

The first database was composed of 539 individual A-scans of known classes at 1 and 2.25 MHz. The signals consisted of 256 samples, sampled at 10 MHz. All signals were individually normalized to a maximum amplitude of 1 in order to minimize the effects of pulser-receiver gain settings. A set of 160 signals chosen randomly from 1 MHz signals was used for training the network, and the rest of the signals were used for testing the performance of the neural network. The training data set included 60 crack, 50 counterbore and 50 rootweld signals. The DWT coefficients of these 160 signals were computed using the Daubechies wavelets with 4 vanishing moments. The first 128 of these coefficients were used to train the MLP and the rest were discarded in order to obtain data reduction. The distribution of these signals is given in Table I.

The performance of the neural network with Database I is presented in Table II. Two separate tests were performed to evaluate the effectiveness of the time scaling procedure as a preprocessing algorithm and that of the DWT as a feature extraction algorithm. In test I, the neural network which was trained with 1 MHz signals was tested on unscaled and scaled 2.25 MHz signals, as well as other 1 MHz signals. The results of test I are presented in Columns I through III. In test II, the same network was trained and tested with the Fourier transform coefficients of the same signals instead of the DWT coefficients. The results of this test are presented in Columns IV and V.

Since the neural network was originally trained with 1 MHz signals, the high performance on the rest of the 1 MHz signals comes as no surprise. The results in Columns II and III, however, illustrate a dramatic boost in the performance of the neural network when tested with the scaled 2.25 MHz signals. The results presented in Columns IV and V illustrate the effectiveness of DWT over Fourier transform as a feature extraction algorithm. It is apparent from Table II that the performance of the neural network is optimized when used with time scaling as a preprocessing algorithm and DWT as a feature extraction algorithm.

Database II

The second database consisted of 16 C-scan images of piping welds obtained using 1 and 2.25 MHz transducers. Each C-scan was composed of 121*101 =12,221 A-scans obtained by automated raster scanning of an area of 3'' in the axial direction and 10'' in the circumferential direction. The A-scans were collected with a resolution of 0.025'' in the axial direction and 0.1'' in the circumferential direction. The A-scans sampled at 25 MHz contained 1798 samples. They were segmented using a 256 long window such that the maximum amplitude of the reflected waveform appeared in the middle of the time window. These signals were also normalized to a maximum amplitude of 1.

The first 128 DWT coefficients, obtained using the Daubechies wavelets with 4 vanishing moments, were used to train and test the network. 1000 randomly selected signals were used in the training data set.

Figure 7 shows a typical example from this database with its corresponding neural network generated classification image. In the neural network generated classification image, black represents background, dark gray represents crack, gray represents counterbore, and light gray represents rootweld. The neural network correctly identified all regions of crack, counterbore and rootweld.

Database III

The third database also consisted of C-scan images, obtained using manual raster scanning of an area of 3'' (axially) by 6'' (circumferentially) with the same resolution as in Database II. The signals were obtained using 1.5 MHz transducers, and they sampled at 25 MHz. This database was used in order to test the robustness of the approach to databases obtained using different inspection hardware. The same network trained with Database II was used to test the performance on this database. the original C-scan.

Table I. Distribution of signals in Database I.

Frequency	# of crack signals	# of counterbore signals	# of rootweld signals
1 MHz	98	73	75
2.25 MHz	107	94	92

Table II. Neural network performance with DWT and time scaling.

	Correct Classification (%)				
	DWT			FFT	
	Column I	Column II	Column III	Column IV	Column V
SIGNAL	1 MHz	Unscaled 2.25 MHz	Scaled 2.25 MHz	1 MHz	Scaled 2.25 MHz
Crack	96 %	34 %	93 %	84 %	76 %
Counterbore	100 %	20 %	97 %	86 %	67 %
Rootweld	95 %	61 %	96 %	87 %	95 %

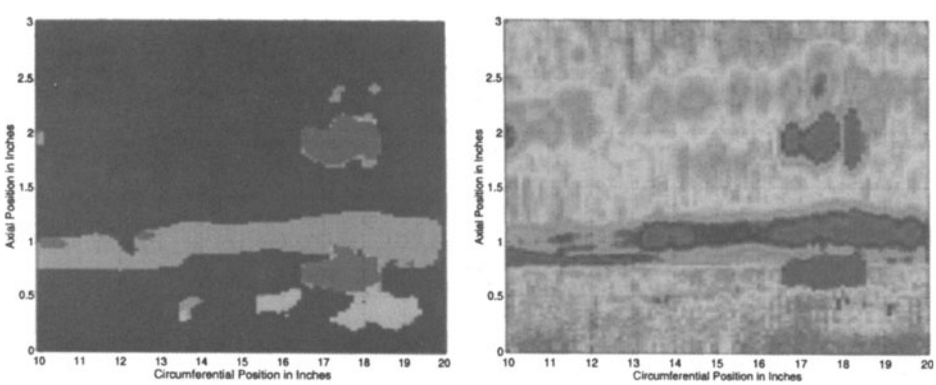

Figure 7. (a) 2.25 MHz C-scan image, (b) Neural network generated image.

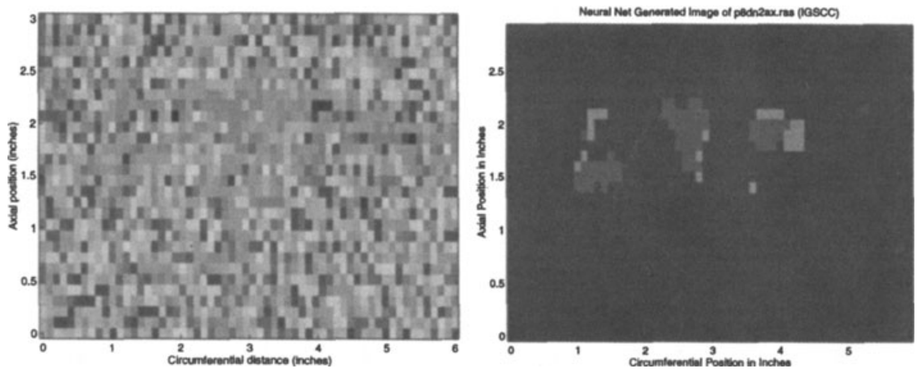

Figure 8. (a) 2.25 MHz C-scan image, (b) Neural network generated image.

All signals were time scaled to 1 MHz from 1.5 MHz prior to testing. Figure 8 illustrates the results on a typical image from this database. The neural network correctly identified all crack regions that were present in the specimen, which was difficult to observe from

CONCLUSIONS

The results obtained to date demonstrate the validity of the overall approach that employs time scaling as a preprocessing scheme to obtain frequency invariance, the DWT as a feature extraction algorithm, and the MLP neural network as a classification algorithm.

The ASC system developed in this study is currently being enhanced to include features that allow the network to predict its own accuracy and reliability. This system is also currently being evaluated by the Electric Power Research Institute, and future plans include participation in the *Performance Demonstration Initiative (PDI)* organized by EPRI to test level 3 ultrasonic inspectors.

ACKNOWLEDGMENTS

This work was supported by Electric Power Research Institute (EPRI) under contract RP3148-06. Project manager: J. Spanner.

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